International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8714-8725

https://doi.org/10.70517/ijhsa463745

Utilization of Deep Deterministic Policy Gradient (DDPG) Algorithm in Predicting the Impact of Macroeconomic Policies on the Stock Market

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Abstract Macroeconomic policies play a very important role in the development of the stock market. The impact of macroeconomic policies on the stock market is complex and nonlinear, and it is difficult for existing models to accurately predict.In order to improve the level of investment decision-making, this paper uses the deep deterministic policy gradient (DDPG) algorithm to study its application in predicting the impact of macroeconomic policies on the stock market. Through the collection of macroeconomic policies and historical stock data, an intensive learning model is established to predict changes in the stock market based on macroeconomic policies as environmental variables. After training the DDPG algorithm, the model learns the influence mechanism. The experiment analyzed from the three dimensions of volatility, prediction accuracy and return on investment. Compared with the SVM (Supported Vector Machine) and RF (Random Forest) algorithms, the average accuracy rate of the DDPG algorithm was 7.8% and 9.6% higher. Therefore, the DDPG algorithm can more accurately understand and grasp the impact of macroeconomic policies on the stock market, and effectively improve the level of investment decision-making and the rate of return. This article conclusion is of great significance to guide investors to make rational stock investment, and it also contributes to the healthy and stable development of the stock market.

Index Terms Macroeconomic Policies, Stock Market, Deep Deterministic Policy Gradient, Reinforcement Learning, Investment Decision-making

I. Introduction

The stock market is increasingly impacted by macroeconomic policies as a result of the trend toward global economic integration [1], [2]. To raise the standard of investment decision-making, it is crucial to research the intricate linkages between them. High-dimensional data is difficult for traditional approaches to analyze, but the advent of deep learning and reinforcement learning (RL) has given rise to a fresh approach [3]. Specifically, the DDPG algorithm can successfully handle the difficulties of ongoing decision-making and extract stock market dynamics from multifaceted economic factors. Promoting the stock market's steady growth and understanding its fluctuations and hazards are extremely important.

The changes in macroeconomic policies have a profound impact on the dynamic development of the stock market, and accurate analysis and prediction have become the key path to avoiding risks [4], [5]. With the evolution of economic theory, research on how macroeconomic policies affect the stock market has become increasingly in-depth. For example, Celebi Kaan's research reveals that in the post crisis era, macro driven markets are more common, and there are more economic variables and indicators that have a significant impact on stock returns during the crisis period [6]. Alam Isbat used multiple regression analysis to empirically test the complex relationship between macroeconomic factors and stock markets in China and Pakistan from 1995 to 2019. The results show that there is a substantial correlation between macroeconomic factors and stock market returns, but some correlations are not significant. Specifically, there is a certain correlation between GDP and the performance of the stock markets in both countries, but the degree of impact varies [7]. Pal Santana used a vector autoregression model to explore the effects of monetary and macroeconomic policies on the Indian stock market. The conclusion points out that the impact of monetary policy on the stock market is particularly significant, surpassing other macroeconomic shocks [8]. Scholars such as John Emmanuel Isaac and Al Kandari Ahmad M have also conducted in-depth research on the relationship between stock markets and macroeconomic factors in different countries and regions [9], [10]. These studies collectively reveal the complex interaction between macroeconomic policies and the stock market. However, when exploring the impact of macroeconomic policies on the stock market, the dynamic characteristics of the stock market itself are often overlooked.

The DDPG algorithm is highly suitable for handling decision problems involving continuous actions and continuous time steps, providing a new approach for studying how macroeconomic policies affect complex and volatile stock markets [11], [12]. The deep deterministic policy gradient recommendation framework proposed by Gao Tianhan, combined with deep cross networks, can effectively train recommendation models and capture cross correlations between data through both deep and cross networks. Experimental results have shown that this method outperforms other baseline techniques in terms of training fitting [13]. Zhang Zhizheng further developed DDPG and proposed asynchronous scenario DDPG, which can achieve efficient learning in a shorter time, improve sampling efficiency, shorten learning time, and enhance effectiveness [14]. The DDPG algorithm is stable and has a fast convergence speed, which can clearly reveal the mechanism of macroeconomic policies on the stock market. However, the complexity of the model remains a current challenge.

In order to accurately grasp the dynamic development of the stock market and improve the scientificity of investment and trading, this article combined the DDPG algorithm to conduct in-depth research on its application in predicting the impact of macroeconomic policies on the stock market. To verify its effectiveness, experiments were conducted at three levels: analysis of volatility impact, prediction accuracy, and analysis of investment return. From the analysis of the volatility impact, it can be seen that there was a certain correlation between macroeconomic policies and the stock market in the time series from 2000 to 2020, with a significance result of 0.001 and a correlation result of 0.577. From the prediction accuracy results, the DDPG algorithm model had a more ideal fitting effect, and the average accuracy was 7.8% and 9.6% higher than the SVM and RF algorithm models, respectively. From the results of investment return analysis, it can be seen that investment strategies predicted based on the DDPG model achieved higher investment returns compared to the other two types of models. In practical applications, the DDPG method can accurately predict and understand the impact of macroeconomic policies on the stock market, effectively improve the decision-making level of investors, and promote the healthy development of the stock market environment.

II. Prediction of the Impact of Macroeconomic Policies on the Stock Market

In the securities market, the macroeconomic policies of the government have two main means of regulating the stock market: one is to regulate through fiscal policy (regulating taxes, expanding fiscal expenditure, transferring payments, issuing treasury bond, etc.), and the other is to regulate through monetary policy (benchmark interest rates and money supply) [15], [16]. In the upward phase of the economy, policy and regulatory departments take relaxed measures to apply favorable fiscal and monetary policies into the market, creating a favorable external environment for the business development of enterprises. Abundant fiscal and monetary policies, as well as a relaxed economic environment, promote an increase in stock market price data, while conversely, it brings downward pressure to stock market price data.

II. A. Data Collection and Preprocessing

Based on the impact mechanism of macroeconomic policies on the stock market, this article collects macroeconomic policy data (GDP, Consumer Price Index (CPI), interest rate data, exchange rate data) and historical stock market price data (closing price, highest price, lowest price) as the objects of data collection.

The collected macroeconomic policy data and historical stock market price data are cleaned up. For partially missing data, the most recent complete data is selected for reuse. In the actual cleaning process, for the values lost on the T-th day, the data from the $\mathrm{T}-1$ and $\mathrm{T}-2$ days are queried to determine if they are complete. If they are complete, they are used until reusable data is found. For outliers, a box plot is used to exclude data outside the mean ±3×standard deviation range and treat them as outliers. The duplicate values are determined by sorting and classifying the data, and after identifying the duplicate values, they are directly deleted.

Due to the fact that economic policy data is often monthly, it has low-frequency characteristics [17]. The historical price data of the stock market is mostly daily data, with high frequency [18]. Therefore, this leads to differences in data frequency. In terms of preprocessing, this article adopts the Generalized Autoregressive Conditional Heteroskedasticity-Mixed Data Sampling (GARCH-MIDAS) model for processing, as shown in Figure 1:

In Figure 1, the GARCH-MIDAS model is used to align high-frequency and low-frequency data by utilizing the complementarity of data at different frequencies, in order to fully explore the information contained in high-frequency data and enrich the features of low-frequency data.

The model structure is represented by the formula [19], [20]:

$$d_{i,t} = \mu + \sqrt{v_{i,t}}\varepsilon_{i,t}, \forall i = 1, \cdots, C_t \tag{1}$$

The definition of variables in Formula 1 is shown in Table 1:

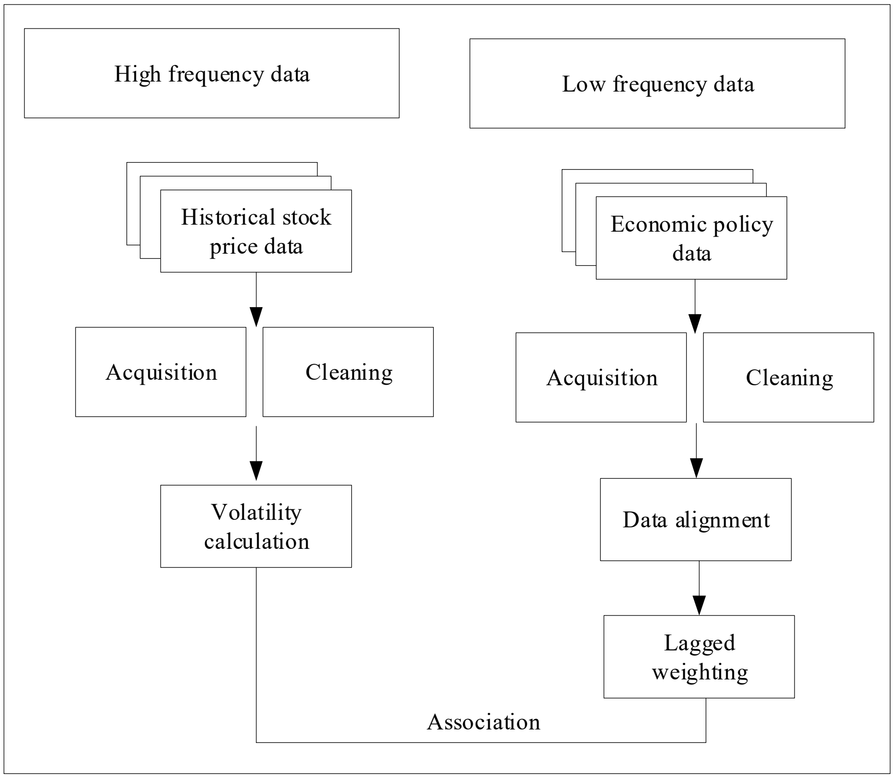

Figure 1: GARCH-MIDAS model

Table 1: Definition of variables in Formula 1

Sequence	Variables	Meaning
1	$d_{i,t}$	Historical stock market price data on the i-th day of the t-th cycle
2	μ	Mean value of economic policy practice sequence
3	$v_{i,t}$	Stock market volatility
4	$\varepsilon_{i,t}$	Model random disturbance term
5	C_t	Days within the cycle

In Table 1, $v_{i,t} = v_t^l \cdot v_{i,t}^s$. Among them, v_t^l represents the long-term volatility in the t-th cycle; $v_{i,t}^s$ represents the short-term volatility on the i-th day in the t-th cycle, and its distribution is expressed by the formula:

$$\varepsilon_{i,t} \big| \varphi_{i-1,t} \sim N(0,1) \tag{2}$$

Among them, $\varphi_{i-1,t}$ is sourced from historical data.

For the component of short-term volatility, it is assumed that it is a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) structure, expressed with the formula [21]:

$$v_{i,t}^s = (1 - \alpha - \beta) + \alpha \frac{(d_{i-1,t} - \mu)^2}{v_t^l} \tag{3}$$

The constraint conditions of Formula 3 are consistent with the GARCH model, satisfying $0 < \beta < 1$ and $0 < \alpha + \beta < 1$. Here, the long-term component benchmark formula for v_t^l is constructed based on achievable volatility on a monthly or quarterly basis, represented as [22], [23]:

$$v_t^l = I + \delta \sum_{k=1}^{K} \Phi_k(w_1, w_2)\, v'_{t-k} \tag{4}$$

$$v'_{t-k} = \sum_{i=1}^{C_t} d_{i,t}^2 \tag{5}$$

The definitions of variables from Formula 4 to Formula 5 are shown in Table 2:

Table 2: Variable definitions for Formula 4 to Formula 5

Sequence	Variables	Meaning
1	I	Intercept
2	δ	Regression coefficient
3	$\Phi_k(w_1, w_2)$	Weighting function
4	v'_{t-k}	Realized volatility with lagged k-period

Formula 5 is the basic calculation formula for volatility completed in a cyclical cycle, which is the sum of squares of daily returns in a cyclical cycle.

To improve data utilization and achieve smoother model fitting, the long-term volatility components are logarithmically processed:

$$\log v_t^l = I + \delta \sum_{k=1}^{K} \Phi_k(w_1, w_2)\, v'_{t-k} \tag{6}$$

II. B.RL Model Construction

The environment refers to the sum of various factors that macroeconomic policies affect the development of the stock market, and it has a certain effect on the rise and fall of stock prices. The collected data is processed using the GARCH-MIDAS model to form a feature vector that can represent multi-source data. Then, using macroeconomic policies as environmental variables and changes in the stock market as the target for prediction, an RL model is established, as shown in Figure 2:

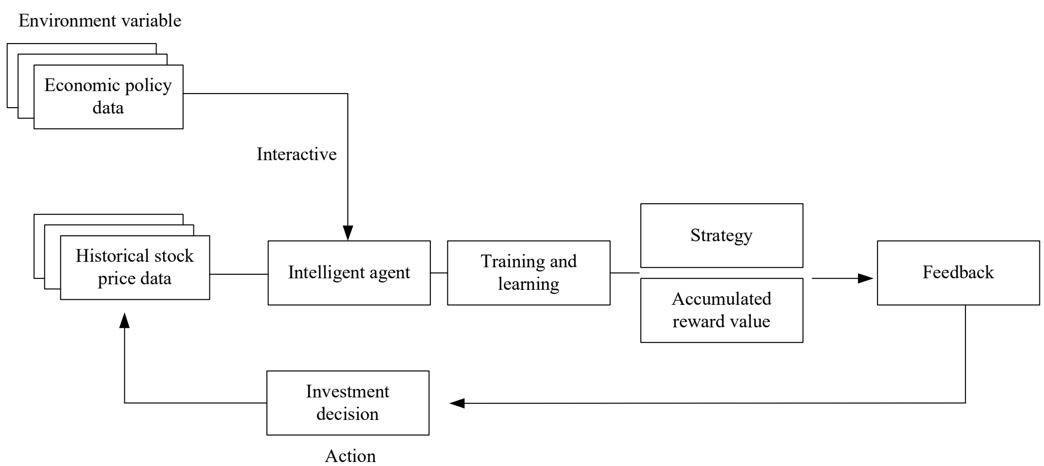

Figure 2: RL model

In Figure 2, the interaction between the intelligent agent and the environment is used to dynamically predict the impact of macroeconomic policies on the stock market, thereby helping investors make better investment decisions. This process is abstracted as Markov Decision Process (MDP):

$$\mathrm{MDP} = (\mathrm{S}, \mathrm{A}, \mathrm{P}, \mathrm{R}, \gamma) \tag{7}$$

The definition of variable in Formula 7 is shown in Table 3:

Table 3: Definition of variables in Formula 7

Sequence	Variables	Meaning
1	S	State space
2	A	Action space
3	P	State transition probability function
4	R	Reward function
5	γ	Discount factor

Based on Table 3, the state space, action space, and reward function are designed.

State is a characterization of the current stock market environment, which enables RL entities to obtain information from the stock market. Therefore, in order to better understand the changes in the stock market, it is necessary to add more variables containing policy data to the model. This article selects GDP, CPI, interest rates, and exchange rates as environmental variables, and uses historical stock market price data as feedback on the external environment.

Actions represent intelligent agents describing implementable behaviors in the environment in a dynamic and interactive manner [24], [25]. The design of action spaces takes into account the feasibility, controllability, and interaction and limitations between investors or decision-makers in practice. On this basis, the investment decision action is defined as $a\epsilon\{-1,0,1\}$. The final action output of the strategy network is a three-dimensional vector representing the likelihood of different actions occurring.

Reward is the dynamic interaction between an agent's action and the environment during the execution of a decision, in which the environment continuously rewards the agent [26], [27]. During this period, by calculating the rewards for cumulative behavior, with the goal of maximizing cumulative rewards, the optimal strategy is sought. The strategy function is defined as $\rho(s)$, which represents the mapping from state space to action space. Deterministic policy gradient refers to seeking a deterministic action in a certain state, in order to transform the current state s into a new state $s^{'}$. On this basis, the definition of cumulative rewards is:

$$\max_{\rho(s)}[\textstyle\sum_{k=0}^{\infty}\gamma^{k}\, r_{t+1+k}] = \max_{\rho(s)}[R_t = r_{t+1} + \gamma r_{t+2} + \cdots] \tag{8}$$

Among them, $\gamma\epsilon(0,1)$, and r_t represent the reward at time t.

The reward function is closely related to the generation of rewards, and rewards have an impact on strategies, balancing the different preferences and goals of investors, and considering the stability and convergence of intelligent agent learning. For investment portfolios, three different functions (investment performance, stock market risk, and policy consistency) are set up to calculate rewards. Among them, the investment performance reward function is expressed as:

$$R_{Profit}(s,a,s^{'}) = Profit(s^{'}) - Profit(s) \tag{9}$$

Among them, $Profit(s)$ represents the portfolio performance under state s, which refers to the return or cumulative return of the securities portfolio.

The stock market risk reward function is expressed as [28]:

$$R_{Marketrisk}(s,a,s^{'}) = \alpha \cdot Marketrisk(s^{'}) - \beta \cdot Marketrisk(s) \tag{10}$$

Among them, $Marketrisk(s)$ represents the market risk measured by the stock market volatility index in state s.

The policy consistency reward function is expressed as:

$$R_{consistency}(s,a,s^{'}) = -\lambda\|P_t - A_t\|^2 \tag{11}$$

Among them, P_t represents macroeconomic policy data during the cycle, and A_t represents investment and trading activities during that cycle. λ is a hyperparameter value used to adjust the proportion of policy consistency rewards in the total rewards.

Under the processing of three reward functions: investment performance, stock market risk, and policy consistency, real-time rewards are calculated, and cumulative rewards are then calculated. Finally, the cumulative reward value for a period of time is obtained, which is then used to feedback the strategy network until the optimal investment strategy is found.

II. C.Implementation of DDPG Algorithm

An adaptive decision-making method based on DDPG is used, that is, optimal decisions on the actions of intelligent agents are made under certain economic policies, stock markets, and other conditions. Goals are achieved by maximizing cumulative rewards. When predicting the impact of macroeconomic policies on the stock market, the DDPG algorithm is used to train intelligent agents to learn the complex relationship between macroeconomic policies and stock market data, and to predict future stock market trends based on the trained strategies.

The DDPG algorithm adopts two Actor-Critic models: the former accepts state values to generate subsequent actions, and the latter is used to evaluate the generated actions. The Critic network is updated based on the difference between executing and not executing actions.

The Actor-Critic network adopts a deep neural network composed of fully connected layers, and its variable settings and network structure settings are shown in Tables 4 and 5:

Table 4: Actor-Critic network variable settings

Sequence	Variables	Meaning
1	Actor's current network	$\zeta_i(o_i)$
2	Current network parameters	θ_i
3	Actor's target network	$\zeta_i^{'}(o_i)$
4	Target network parameters	$\theta_i^{'}$
5	Critic's current network	$Q_i^{\zeta}(s, a_1, \cdots, a_n)$
6	Critic's target network	$Q_i^{\zeta'}(s, a_1, \cdots, a_n)$

Table 5: Network structure settings

Sequence	Network structure	Number of nodes
1	Network input layer	6
2	The first hidden layer	128
3	The second hidden layer	64

According to Tables 4 and 5, let $s = (o_1, \cdots, o_n)$. The algorithm framework is shown in Figure 3:

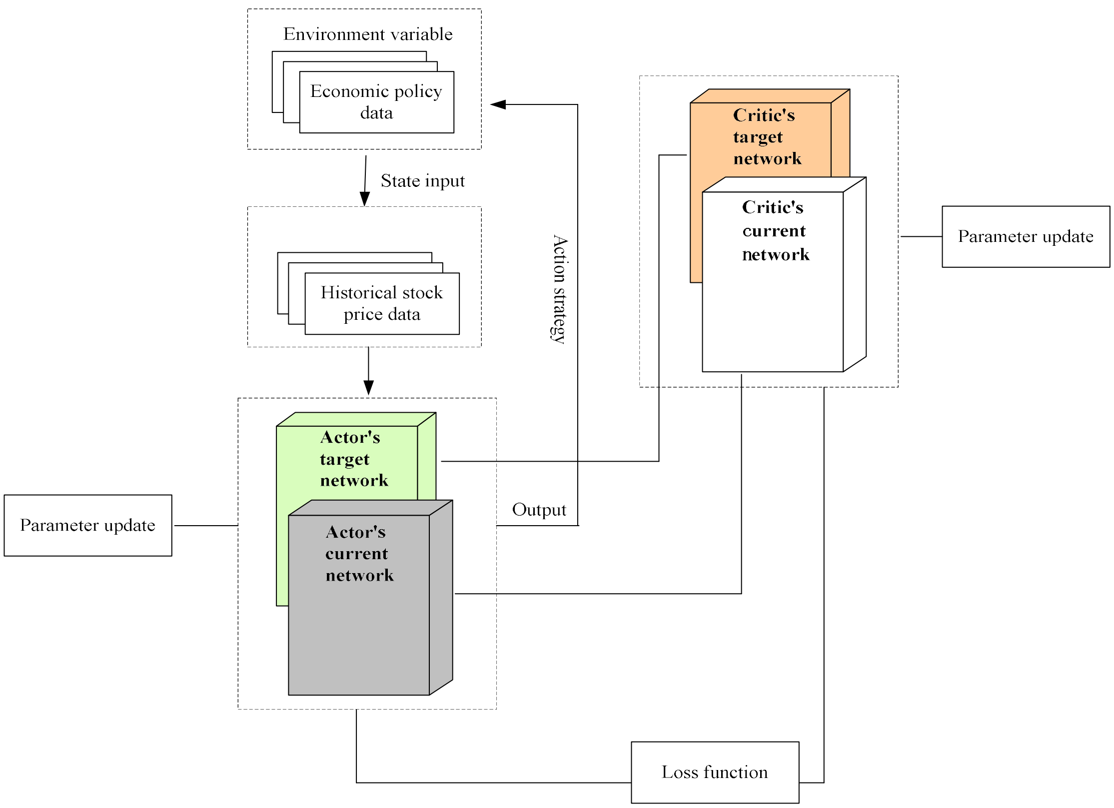

Figure 3: DDPG algorithm framework

The optimization objective of the policy network (Actor) of the DDPG algorithm is to maximize $Q_i^{\zeta}(s, a_1, \cdots, a_n)|a_i = \zeta_i(o_i)$, with a gradient of [29]:

$$\nabla_{\theta_i} g(\zeta_i) = \mathrm{E}_{s,a \sim D}\left[\nabla_{\theta_i}\zeta_i(o_i)\nabla_{a_i}Q_i^{\zeta}(s, a_1, \cdots, a_n)\right]|a_i = \zeta_i(o_i) \tag{12}$$

Among them, D is an experience feedback pool, and $(s, s^{'}, a_1, \cdots, a_n, r_1, \cdots, r_n)$ is used to represent an experience tuple. It should be noted that s, a are both extracted simultaneously from the experience feedback pool. Therefore, when substituting into the Q function, only a_i can be recalculated, allowing the gradient to flow into the policy network; of course, with all the latest policy networks known, it is also possible to recalculate all behaviors, but this may increase the training cost.

The update of the Critic network is similar to the Deep Q-Network, except that the selection of a_i is achieved through the participant target network, the rest is achieved by the Critic network. During this process, optimization is carried out with the goal of reducing the value of the loss function:

$$L = E_{s,a,r,s'}\left[\left(Q_i^{\zeta}(s, a_1, \cdots, a_n) - \gamma\right)^2\right], y = r_i + \gamma Q_i^{\zeta'}(s', a_1', \cdots, a_n')|a_k' = \zeta_k'(o_k) \tag{13}$$

In practical applications, multi-layer perceptrons are widely used in multi-agent reinforcement learning. However, when intelligent agents are trained separately, the same initial observation and action may correspond to different rewards and subsequent observations, achieving coexistence in experience replay [30]. That is to say, facing the same observation and action, the rewards and observation results obtained are completely different, which is detrimental to the training of intelligent agents. In addition, Critic only trains through local observations (that is, agent observations), which may result in poor training and learning performance due to not considering the behavior of other individuals. In algorithms, using a centralized Critic strategy can not only solve conflicts in the experience feedback process of intelligent agents, but also effectively solve the problem that the Critic network cannot directly focus on other intelligent agents during the training process. After training, the complexity of prediction analysis is greatly reduced due to the fact that the Actor network only needs to perform local observations.

III. Experimental Tests of DDPG Algorithm

III. A. Experimental Data

Considering the completeness and availability of macroeconomic policy data and historical stock market price data during the corresponding period, this article selected the raw data from January 2000 to December 2020 as the sample set. Among them, the historical price data of the stock market was divided into cycles using data from the Shanghai Stock Exchange Composite Index (SSE Composite Index), and the macroeconomic cycle was described using the business index of macroeconomic. The historical stock market prices were sourced from the Wind database. The macroeconomic coincident index (CI) was sourced from the websites of the National Bureau of Statistics and the People's Bank of China. To verify the application effect of the DDPG algorithm in predicting the impact of macroeconomic policies on the stock market, experimental tests were conducted from three dimensions: volatility impact analysis, prediction accuracy, and investment return analysis.

III. B. Experimental Results

(1) Volatility impact

To analyze the predictive performance of DDPG, first, the raw data collected from January 2000 to December 2020 were subjected to volatility impact analysis, as shown in Figure 4:

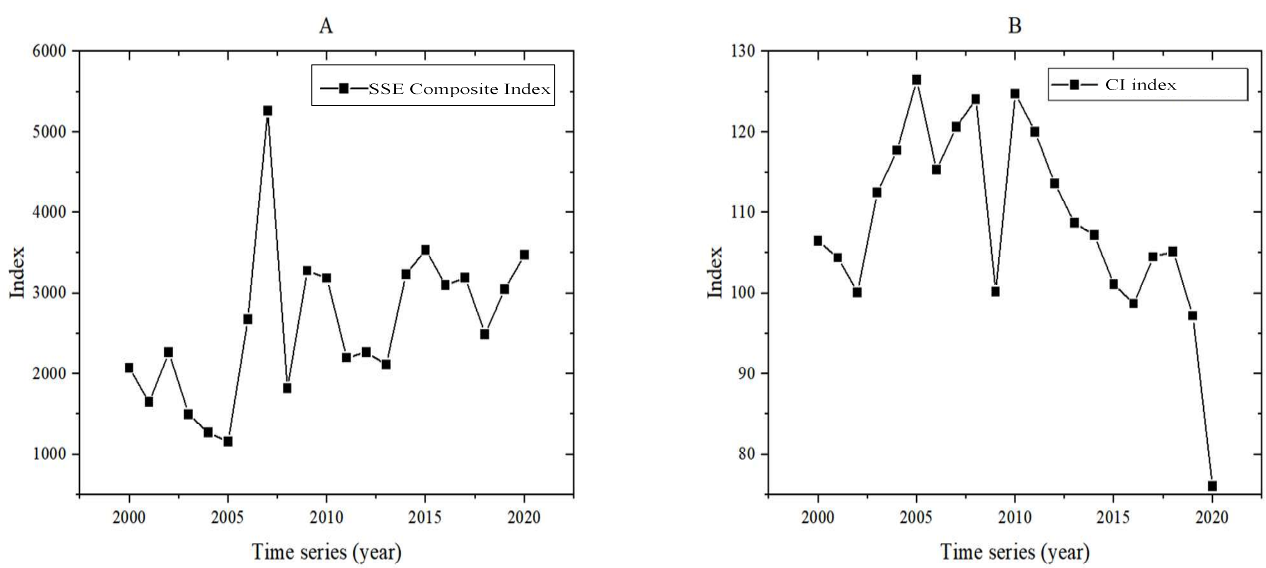

Figure 4: Analysis results of volatility impact

Figure 4A shows the volatility of SSE Composite Index;
Figure 4B shows the volatility of macroeconomic CI.

According to the analysis of the volatility impact in Figure 4, the SSE Composite Index volatility and macroeconomic CI volatility were divided by cycles. Among them, the SSE Composite Index volatility was divided into four cycles: the first cycle was from January 2000 to June 2005; the second cycle was from July 2005 to December 2008; the third cycle was from January 2009 to June 2014; the fourth cycle was from July 2014 to December 2020. The macroeconomic CI volatility was divided into two cycles: the first cycle was from January 2000 to December 2009; the second cycle was from January 2010 to December 2020.

In Figure 4A, the SSE Composite Index fluctuated less in the first cycle, with an index range of 1000-2500. In the second cycle, the index fluctuated sharply. In 2008, due to the impact of the financial crisis and the weakness of the global economy, the index showed a sharp decline. In the third cycle, the index level slowly recovered, mainly due to the macroeconomic stimulus policies formulated in response to the financial crisis. In the fourth cycle, the index closed at 3473.07 in December 2020, which was within a relatively high range throughout the entire cycle.

In Figure 4B, macroeconomic CI benefited from reforms and was stimulated by favorable economic policies in the first cycle, with index levels reaching over 100 and reaching its highest point in 2005. In the second cycle, due to the overall decline of the world economy, the production capacity structure was still in the process of transformation and development. The macroeconomic CI was 76.0 in December 2020, which was the lowest point in the range.

To analyze the correlation between the two, SPSS software 13.0 was used for statistical analysis. The final results are shown in Table 6:

Table 6: Statistical analysis results

Item		Macroeconomic CI	SSE Composite Index
Macroeconomic CI	Pearson correlation	1	0.577
	Significance	-	0.001
SSE Composite Index	Pearson correlation	0.577	1
	Significance	0.001	-

From Table 6, the correlation result was 0.577, and the significance result was 0.001, indicating that macroeconomic policies have a significant impact on the stock market from 2000 to 2020.

(2) Prediction accuracy

Based on the analysis of the impact of volatility in Figure 4, the overall return rate, which can reflect the volatility in the entire stock market, was selected as the indicator and used as the prediction target. All observations were divided into training and testing sets. Among them, the training set was used for fitting analysis of stock market volatility; the testing set was used to predict stock market volatility. The algorithm training parameter settings are shown in Table 7:

Table 7: Algorithm training parameters

Sequence	Parameter	Specifications
1	Learning rate	0.001
2	Batch size	64
3	Periodization	100
4	Attenuation factor	0.99
5	Soft update factor	0.005
6	Weight initialization method	Xavier
7	Noise variance	0.2
8	Variance decay rate	0.9995

Based on the training parameters in Table 7, firstly, the DDPG algorithm was adopted to train the intelligent agent, and the experience replay method was adopted to store the experience of each stage in the experience replay buffer. By using random sampling, a batch of data was extracted from a set of experience replay caches at certain time intervals for training. The Critic network was used to estimate bias, and the Adaptive Moment Estimation was used to correct the parameters of Actor network and Critic network. The parameters of the target network were updated using a soft update strategy. To verify the predictive performance of the algorithm proposed in this article, it was compared with traditional RF and SVM algorithm models. The fitting effect and final prediction accuracy results are shown in Figures 5 and 6:

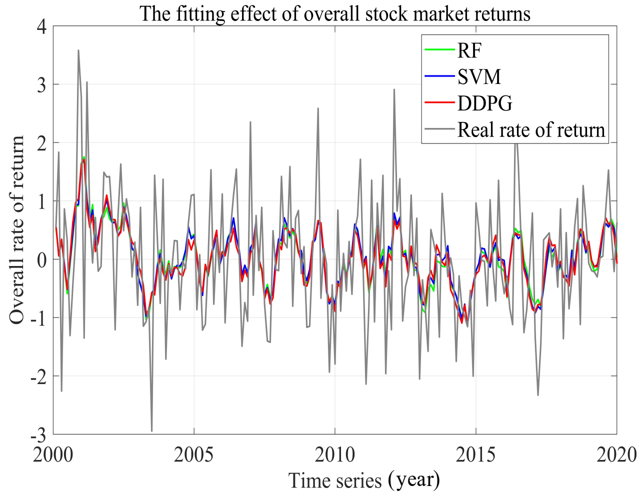

Figure 5: Algorithm model fitting effect

In Figure 5, the three types of algorithms exhibited different fitting effects in the time series. Overall, the fitting results can to some extent reflect the changes in stock market returns under the influence of macroeconomic policies. From the specific comparison results, the overall trend of the DDPG algorithm fitting curve was smoother, and its fitting results were closer to the true values. Compared to the other two types of algorithms, the DDPG algorithm more fully captured the long-term trend of stock market returns. However, methods such as RF and SVM have weak generalization ability for temporal data, making it difficult to effectively mine temporal data, resulting in significant volatility in fitting results during certain time periods and significant deviations from actual data. The DDPG algorithm can better reflect the long-term correlation between economic policies and the stock market, and improve the fitting effect.

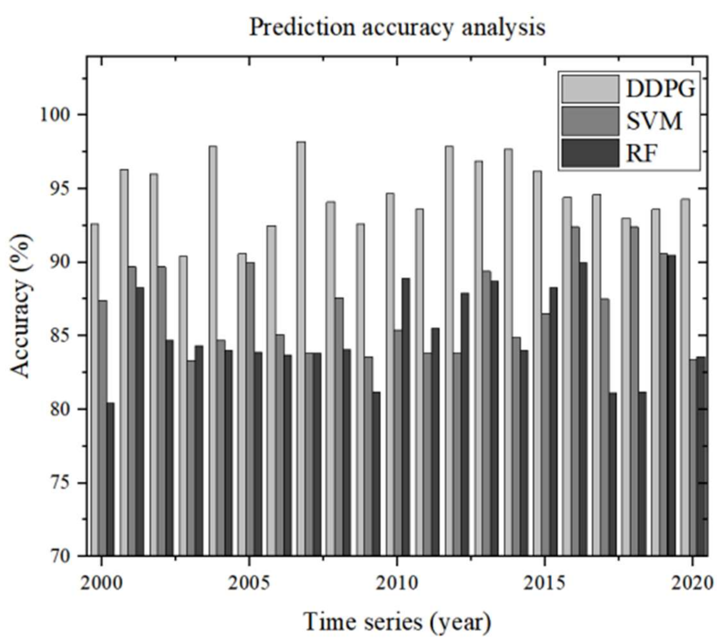

Figure 6: Prediction accuracy results

From Figure 6, it can be seen that the DDPG algorithm model in this article had a significant advantage in accuracy in predicting the impact of macroeconomic policies on the stock market. The highest prediction accuracy of the DDPG algorithm model in the time series was 98.2%, with an average of approximately 94.7%; the highest results of SVM and RF algorithm models were 92.4% and 90.5%, respectively, with average values of approximately 86.9% and 85.1%. From the specific comparison results, in terms of the average accuracy, compared to SVM and RF algorithm models, the DDPG algorithm model in this article was 7.8% and 9.6% higher, respectively. The impact of economic policies on the stock market presents a more complex and dynamic nature. The DDPG algorithm can better explore nonlinear correlations in the stock market through continuous learning and optimization, thereby effectively improving the prediction accuracy of the impact mechanism.

(3) Investment return

Based on the prediction results of the model, the performance of the investment strategy on historical trading data was simulated, and the changes in the value of the investment portfolio were calculated for each trading cycle. The investment return was analyzed using annualized rate of return and maximum drawdown rate as indicators. The calculation formulas are shown in Formulas 14 and 15:

$$Annualized\ return = \left(\frac{value_f}{value_i}\right)^{\frac{1}{z}} \times 100\% \tag{14}$$

Among them, $value_i$ represents the initial value of the investment portfolio; $value_f$ is the final value of the investment portfolio; z is the year.

$$Drawdown = \max_{i,j:i<j}\left(\frac{Drawdown_c - Drawdown_p}{Drawdown_c}\right) \times 100\% \tag{15}$$

Among them, $Drawdown_c$ represents the maximum drawdown cycle value; $Drawdown_p$ is the maximum value during the drawdown period.

According to Formulas 14 and 15, the changes in investment portfolio value predicted by different algorithm models are shown in Figure 7:

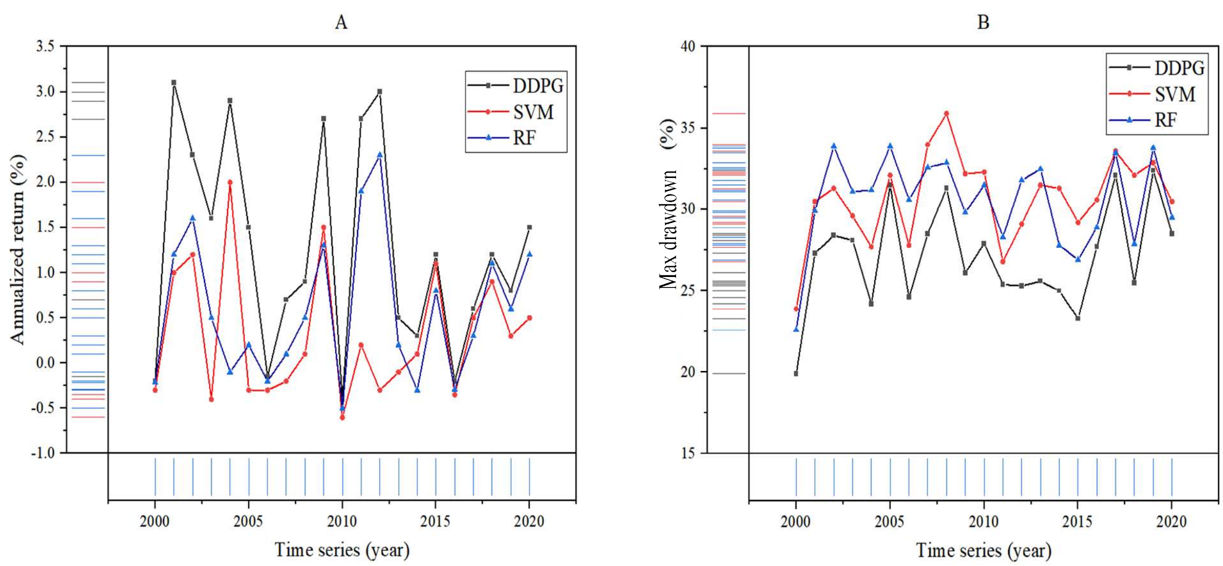

Figure 7: Investment return results

Figure 7A shows the results of the annualized rate of return;

Figure 7B shows the results of the maximum drawdown rate.

In Figure 7, the portfolio value fluctuated significantly among the three types of algorithm models, and there were significant differences. In Figure 7A, based on the prediction results of the DDPG algorithm model, the highest annualized return achieved by the simulated investment strategy in the time series was 3.1%, with an average result of approximately 1.3%; based on the prediction results of SVM and RF algorithm models, the highest annualized returns achieved by simulating investment strategies in time series were 2% and 2.3%, respectively, with average results of about 0.3% and 0.6%. In Figure 7B, the maximum drawdown rate under the DDPG algorithm model was 32.4%, with an average result of approximately 27.1%; the maximum drawdown rates under the SVM and RF algorithm models were 35.9% and 33.9% respectively, with average results of approximately 30.7% and 30.5%. From the overall investment return results, under the prediction results of the DDPG algorithm model, the simulated investment strategy generally achieved higher annualized returns and lower maximum drawdown rates in the time series. This indicates that the DDPG algorithm is more reliable in predicting stock market trends and changes under the influence of macroeconomic policies. Through timely adjustment and optimization, the investment strategy is more robust, effectively improving the value and return of the investment portfolio.

IV. Discussion

In the experimental analysis, this article conducted experimental tests from three dimensions: volatility impact analysis, prediction accuracy, and investment return analysis. In the analysis of volatility impact, the raw data from 2000 to 2020 was divided into cycles. From the statistical analysis results, it can be seen that macroeconomic policies had a significant impact on the stock market in the time series from 2000 to 2020. In terms of prediction accuracy, compared with SVM and RF algorithm models, the DDPG algorithm model achieved more ideal fitting effects and prediction accuracy. In investment return analysis, based on the prediction results of the DDPG algorithm model, its investment return was more ideal compared to the other two types of algorithms, achieving higher annualized returns and lower maximum drawdown rates.

V. Conclusions

In the current context of volatile financial markets and frequent macroeconomic policy changes, the challenges of predicting and making decisions in the stock market are becoming increasingly significant. Traditional financial analysis methods are difficult to accurately and fully understand and predict the impact mechanism of macroeconomic policies on stock market volatility. In order to improve the robustness and reliability of investment decisions and promote the healthy development of the stock market, this article combined the DDPG algorithm to conduct in-depth research on its application in predicting the impact of macroeconomic policies on the stock market. The DDPG algorithm model fully revealed the inherent impact mechanism between macroeconomic policies and the stock market. Based on its prediction results, investment strategy analysis was conducted, effectively achieving an improvement in investment returns. Although the DDPG algorithm can accurately predict stock market volatility to a certain extent, there are still limitations in this study. In future research, it can be considered to explore more ways to improve the practical application effects of algorithms from the perspective of data source characteristics, in order to cope with the ever-changing financial market and enable investors to make more scientific and effective trading decisions.

Funding

This work was sponsored in part by Shandong Provincial Natural Science Foundation. Project “Research on Macro and Micro Mechanisms of PPPs” (ZR2021QG068).

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